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LSTM Neural Network for Beat Classification in ECG Identity Recognition

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ABSTRACT

As a biological signal existing in the human living body, the electrocardiogram (ECG) contains abundantly personal information and fulfils the basic characteristics of identity recognition. It has been widely used in the field of individual identification research in recent years. The common process of identity recognition includes three steps: ECG signals preprocessing, feature extraction and processing, beat classification recognition. However, the existing ECG classification models are sensitive to limitations of database type and extracted features dimension, which makes classification accuracy difficult to improve and cannot meet the needs of practical applications. To tackle the problem, this paper proposes to build an ECG individual recognition model based on a deep Long Short-Term Memory (LSTM) neural network. The LSTM network model has a memory cell and, therefore, it is an expert in handling long time ECG signals. With deeper learning, the nonlinear expression ability of the ECG beat classification model is gradually enhancing. The paper adopts two stacked LSTM models as hidden layers in the neural network; the Softmax layer is used as a classification layer to identify an individual. Then, low-level morphological features and deep-level chaotic features (Lyapunov exponent) are extracted to verify the feasibility of the deep LSTM network for classification. The model is respectively applied to a healthy human database and a human with a heart disease database. Experimental results show that extracting simple low-level features and chaotic features both achieve better classification performance. So, the robustness of the LSTM classification model is verified.

KEY WORDS: Identity recognition, chaotic feature, ECG beat classification, LSTM neural network

1 INTRODUCTION

AN ECG signal is the process of electrical activity recording cardiac pacing; it reflects potential physiological information of the human body (Agrafioti, Gao, & Hatzinakos, 2011). Since an ECG consist of physiological information that exists along with one's life, and the waveforms are various such as an individual's heart size, position, gender, age and other self-factors. The ECG signal represents discriminative identity information among different individuals. As time goes on, the change of each individual's ECG signal is very tiny excluding the organic lesion of the heart. So, the stability of the signal lays a foundation for identity recognition.

The common process of identity recognition includes ECG signals pre-processing, feature extraction, processing, and heartbeat classification recognition (Choi et al., 2019). In previous related research, the key techniques of an individual's ECG identification have achieved a series of progress (Bras, Ferreira, Soares, & Pinho, 2018; Dong, Si, & Huang, 2018; Tan, & Perkowski, 2017; Patro, & Kumar, 2017). For feature extraction of an ECG signal, one is directly measuring the ECG signal to obtain information, which is a low-level feature of the signal (Kannathal, Acharya, Lim, Sadasivan, & Iyengar, 2004; Coutinho, Silva, Gamboa, Fred, & Figueiredo, 2013; Silva et al., 2015); Another technique is deeply mining low-level information of the signal to extract deep-level features of the signal (Ji, & Wu, 2013; Jin, Ping, Mary, Saeid, & Abbas, 2013). Chen et al. (Chen, Xu, & Shen, 2015) extracted fusion features of QRS (Q-wave, R-wave and S-wave) complex and other

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feature points with KPCA (Kernel Principal Component Analysis) to identify. Coutinho et al. (Coutinho, Fred, & Figueiredo, 2010) took average single heartbeat waveforms as a feature input and conducted dimension reduction based on the data compression technique, which is the Ziv-Merhav cross parsing algorithm. Hejazi et al. (Hejazi, Al-Haddad, Singh, Hashim, & Aziz, 2016) used the autocorrelation (AC) algorithm to extract non-fiducial features and kernel methods to reduce the dimension. Though the above literatures can be seen that the ECG signal low-level feature extraction algorithm depends on positioning accuracy of the fiducial points and waveforms, and it cannot deeply express the internal information of the signal. Though the ECG signal deep-level feature extraction algorithm could mine effective information of signals, meanwhile it brings complexity of recognition computation. For the establishment of the heartbeat classification model, commonly adopting such as the supervised classification algorithm, neural network and machine learning model based on the statistical learning theory to identify an individual (Rai, Trivedi, & Shukla, 2013; Zidelmal, Amirou, Ouldabdeslam, & Merckle, 2013; Khazaee, & Ebrahimzadeh, 2013; Moein, Logeswaran, & Faizal bin Ahmad Fauzi, 2016). Kouchaki et al. (Kouchaki, Dehghani, Omranian, & Boostani, 2012) adopted 1NN (nearest neighbor) classifier to recognize the ECG frequency signals obtained by EMD (empirical mode decomposition) decomposition and Hilbert transform. Lin et al. (Lin, Chen, Lin, & Yang, 2014) implemented the nonlinear SVM (support vector machine) with polynomial kernel function to identify the extracted chaotic feature set. Rahhal et al. (Rahhal et al., 2016) built the deep neural network model to classify the ECG signal features that are obtained from SDAEs (stacked denoising autoencoders). Beyli (Beyli, 2009) set up the RNN (recurrent neural network) model to classify ECG heartbeats. Although various classifiers can classify and identify the ECG signal, in the practical application, establishing the deep recognition model with strong robustness and generalization performance will have actual significance.

Aiming at these problems existed in research of the feature extraction and classification. The paper focuses on studying ECG signals and identity the recognition system based on the LSTM network. The Long Short-Term Memory unit was first proposed to improve the traditional RNN model by Hochreiter & Schimidhuber (Hochreiter, & Schmidhuber, 1997). Compared with the RNN, the LSTM network with memory function can effectively solve the problem of exploding and vanishing gradient problems during training, which makes the network suitable for long time series signals. The LSTM type of RNN has been widely applied in fields of handwritten numeral recognition, machine translation, information retrieval and so on in recent years, especially in speech recognition that has achieved great results and significantly reduced the recognition error rate (Bahdanau, Cho, & Bengio, 2014; Palangi et al., 2015; Sutskever, Vinyals, & Le, 2014). In view of the application of LSTM in other fields is effective and suitable for interrelated ECG signals in principle. So, for the classification model, the paper studies to establish the deep LSTM model to identify extracted features of ECG signals.

The conclusion that dynamic characteristics of healthy life system is “chaotic” was proposed by Goldberger (Goldberger, 1996). With the rapid development of nonlinear science, researchers have applied nonlinear systems and the chaos theory to the biological research system. The chaotic characteristic has been found in various kinds of physiological signals such as; blood pressure, EEG (electroencephalogram), EMG (electromyogram) and ECG. The ECG dynamics system is a typical chaotic dynamical (Shekofteh, Jafari, Sprott, Golpayegani, & Almasganj, 2015), method of nonlinear dynamic research that could be adopted to analyze cardiac electric activity. At present the analysis and research of an ECG nonlinear characteristic mainly focuses on a correlation dimension, Lyapunov exponent, approximate entropy, complexity and so on to include parameters. So, for the feature extraction algorithm, the paper introduces the Lyapunov exponent to study chaotic feature parameters of ECG signals, which is a feature input for identity recognition. The system respectively employs low-level features and chaotic deep-level features as the feature input for the LSTM classification model is to verify recognition performance.

For the purpose of building the recognition model with strong robustness, the paper proposes to establish the ECG deep learning model based on LSTM network for training feature data. The network contains two LSTM hidden layers and a softmax layer for classification. The morphological features and chaotic features are as inputs for network to construct an entire system. The subsequent arrangement of the paper is as follows: Section 2 introduces the basic structure and internal principle of the LSTM neural network. Section 3 represents the ECG identity recognition model of the deep LSTM network. Section 4 analyzes experimental results and discussions, and Section 5 states the conclusion and future work.

2 LSTM NEURAL NETWORK STRUCTURE

UNLIKE an ordinary multilayer perceptron, the RNN neural network (Graves, 2012) has cyclic structure in the internal connection, namely hidden layer adds, a self-connection structure, which expresses the temporal relation. The loop network connection enables to effectively utilize the context information. The typical RNN network structure is shown in Figure 1.

As illustrated in Figure 1, cyclic characteristic of the RNN network reflects that the input of each node in the hidden layer contains not only an upper layer output but also a hidden layer output at the previous moment. So, the network enables to deal with sequence data. The input set is marked as $\{x_1, x_2, \ldots, x_t, \ldots\}$, the output set of the network is marked as $\{y_1, y_2, \ldots, y_t, \ldots\}$. The output set of the hidden layer node is marked as $\{h_1, h_2, \ldots, h_t, \ldots\}$, which is calculated based on the node state of the input layer and the previous step in the hidden layer.

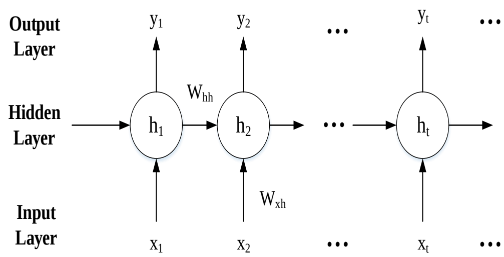

Figure 1. Structure Diagram for One-way RNN Network.

$$h_t = f\left(W_{xh} \cdot x_t + W_{hh} \cdot h_{t-1} + b_h\right) \tag{1}$$

where f is the nonlinear activation function. The output h_t of each hidden layer backward transfers receives a previous layers' information in theory, but actually it is difficult to train deeply. The error gradient of the RNN will gradually decrease to vanish as the number of layers increase, which is leading to the so-called vanishing or exploding gradient problem. The emergence of the RNN network model with the LSTM unit alleviates this problem and enables to clearly express a long-short time dependence relation. The structure of the LSTM network is same as the RNN, only complicating the inner structure of hidden layer unit. The LSTM unit, which is adopted in the paper contains four structures in the memory block; three sigmoid layers and one tanh layer. The memory block structure is shown in Figure 2.

As shown in Figure 2, the LSTM unit solves the vanishing gradient phenomenon through adding a latent variable as the memory cell, so it will overcome the long dependence problem in a time series. The gating mechanism is introduced through input gate i_t, output gate o_t and forget gate f_t. They control information flowing through the cell, that is how much information in the previous network should be kept and how much new information will enter.

$$i_t = \sigma\left(W_{xi} x_t + W_{hi} h_{t-1} + b_i\right) \tag{2}$$

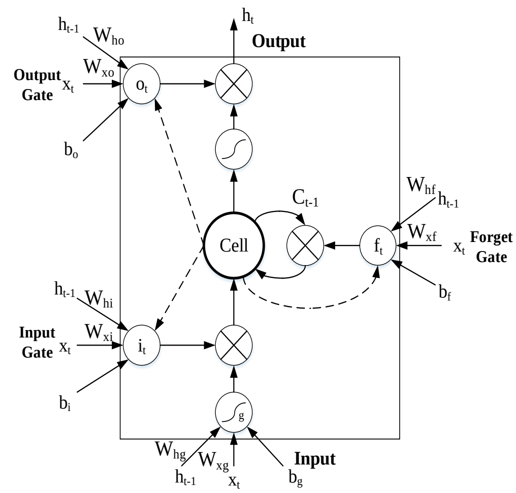

Figure 2. Structure Diagram for Memory Block of the LSTM Unit.

$$f_t = \sigma\left(W_{xf} x_t + W_{hf} h_{t-1} + b_f\right) \tag{3}$$

$$o_t = \sigma\left(W_{xo} x_t + W_{ho} h_{t-1} + b_o\right) \tag{4}$$

$$\tilde{c}_t = \tanh\left(W_{xg} x_t + W_{hg} h_{t-1} + b_g\right) \tag{5}$$

$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t \tag{6}$$

$$h_t = o_t * \tanh\left(c_t\right) \tag{7}$$

Among which, input gate i_t, output gate o_t and forget gate f_t are determined by the sigmoid activation function σ. $\tilde{c}_t$ is the updated value of the memory cell at the current moment. The memory cell state of the previous moment multiplies by the forget gate, which chooses to discard partial information, then adds the updated part to the generate state value of cell c_t at the current moment. Finally, h_t in equation (7) is the final output of the hidden layer for each LSTM network unit.

3 ECG IDENTITY RECOGNITION MODEL BASED ON THE LSTM NETWORK

SINCE the before and after moments the ECG signals are associated and represent correlation for an individual identity. The LSTM network can break through the theoretical limitation of the RNN establishing a long correlative connection among the ECG inputs. The overall block diagram of the ECG identity recognition system based on the LSTM network in the paper is shown in Figure 3.

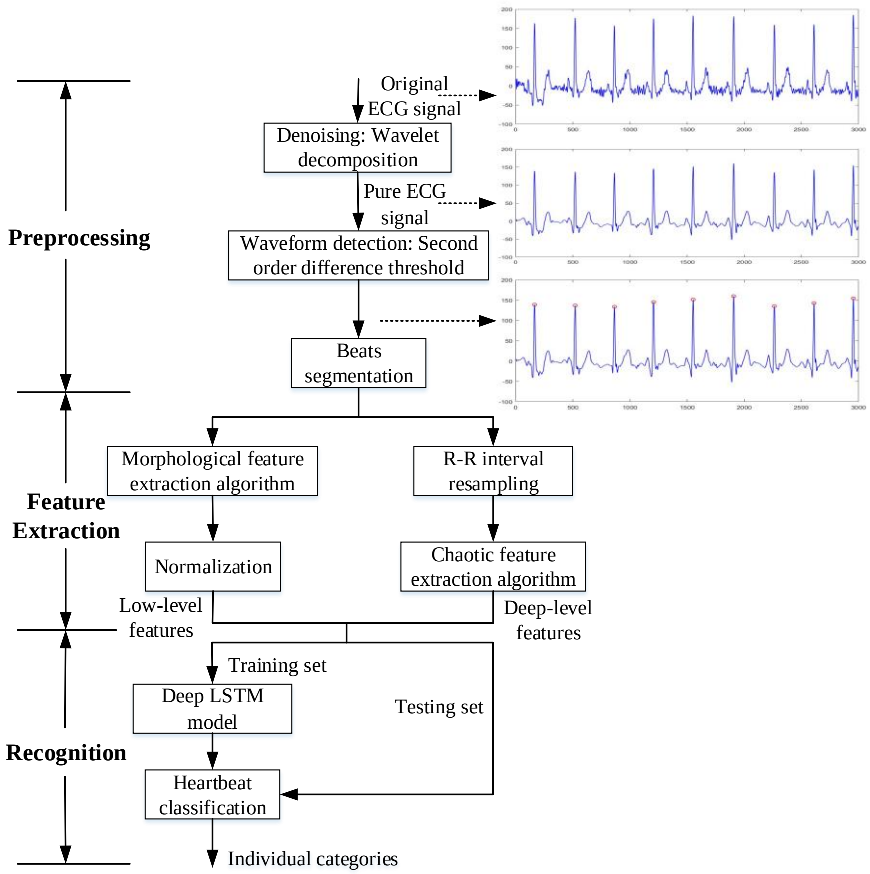

Figure 3. The Overall Architecture of Identity Recognition based on the LSTM Network.

3.1 *Pre-processing*

The original ECG signals with noise are inputted into the system and decomposed into eight layers by the DB4 wavelet lifting. The dynamic threshold setting is conducted according to the frequency distribution of the noise combining with the soft threshold algorithm, so the pure ECG signals, which have been removed from the high frequency noise and baseline drift can be acquired. Compared with the other bands in the ECG signal, the fluctuation characteristic of the QRS complex is more evident, the amplitude and slope of R wave are relatively large. The system uses a second order difference threshold method to detect the R wave peak points. Since the heartbeat is a minimum component unit of the ECG signals, the identity recognition for ECG signals will finally fall on the heartbeat classification, so the ECG signals should be segmented for the subsequent feature extraction.

3.2 *Low-level Feature Extraction of ECG Signals*

The ECG signal is an irregular periodic signal, its waveforms and characteristic parameters could directly reflect different forms of ECG signals among different individuals. Therefore, the ECG signal low-level feature extraction algorithm of the system extracts the whole heartbeat information of signals. The algorithm not only ensures to gain complete information contained in heartbeats but also provides the same dimension feature input for the classified neural network model. Taking the detected R wave peak position as the center, 120 sampling points are chosen forward and behind, together with R wave peak amplitude and R-R interval, so there are 243 dimensions of morphological low-level features. These extracted characteristic points of the ECG signals not only add morphology of the P wave and the T wave but also keeps the influence of different heart rates for waveforms. The morphological low-level features of the five different individuals and five heartbeats of the same individuals are extracted as shown in Figure 4.

As shown in Figure 4, this low-level feature extraction method of the system describes discriminative information among different individuals and correlative information in the same individual. Then the extracted low-level features are performed and normalization to guarantee the value of the features within [-1,1] and prevents data to overflow during iterations.

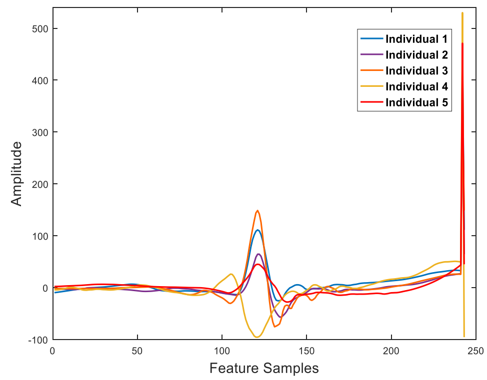

Figure 4(a).

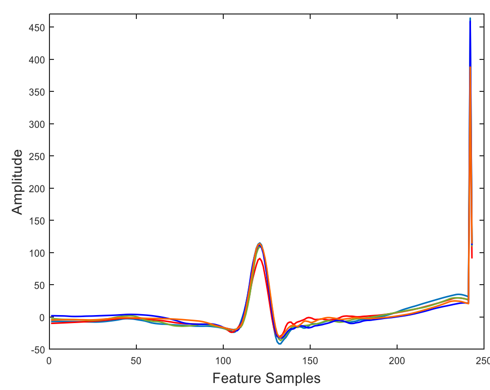

Figure 4(b).

Figure 4. Comparison for Low-level Features of Different Individuals and Same Individuals.

3.3 Chaotic Feature Extraction of ECG Signals

Nonstatistical characteristics of physiological signals, that is chaotic feature parameters, provide new direction for internal analysis and study of physiological signals obtained by the chaos theory. The Lyapunov exponent can measure sensitivity of initial conditions for the chaotic signals motion and describe the average index rate of convergence or divergence for adjacent orbits in phase space (Allshouse & Peacock, 2015). The value of the nonlinear dynamic parameter indicates the chaotic degree of the system and deeply analyzes chaotic ECG signals. The paper employs the Wolf algorithm to get the Lyapunov exponent sequence of the ECG time series as chaotic feature parameters.

Resampling the segmented R-R interval time series of the ECG signals to 300 points so that it is convenient for the subsequent deep-level chaotic feature extraction. The resampling ECG time series $x(t)$ are performed as phase space reconstruction. The embedded dimension m and delay-time τ are respectively determined by the G-P algorithm (Grassberger, 1983) and the mutual information method (Fraser & Swinney, 1986), namely the dimension and delay of reconstructed phase space, so the reconstructed phase space is $\{x(t_i), x(t_i+\tau), \ldots, x(t_i+(m-1)\tau)\}$, $i=1,2,\ldots$ and the correlation integral is calculated as:

$$C(r) = \lim_{N\to\infty} \frac{1}{N^2} \sum_{i,j=1, i\neq j}^{N} H\left(r - \|x_i - x_j\|\right) \quad (8)$$

where $\|x_i - x_j\|$ is distance between two points in the phase space, $C(r)$ represents the cumulative distribution function, r is correlation length and H is Heaviside step function. Within proper range for r, there is the logarithmic linear relationship between attractor dimension d and cumulative distribution function $C(r)$.

$$d(m) = \frac{\ln(C(r))}{\ln(r)} \quad (9)$$

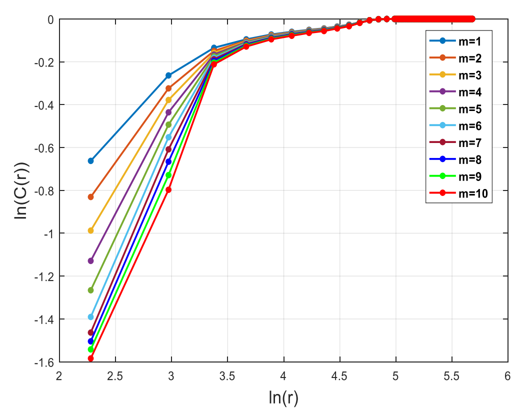

Figure 5. ln (C(r))-ln(r) Curves for Various m Values of ECG Signals R-R interval.

The resampling ECG local sequences are used as input signals. Utilizing the G-P algorithm to test, that taking m from 1 to 10, the simulation of $\ln(C(r)) - \ln(r)$ curves is shown in Figure 5. It is evident from Figure 5 that with m increasing, the slope of the curve will raise. When $m=6$, the slope will not change, that is parallel curves. So $m=6$ is the optimal dimension of the reconstructed space of ECG signals R-R interval. At the same time, the optimal delay-time τ will be selected when the first minimum value appears in the mutual information function between reconstruction of two components with delayed relation.

Find the nearest point $Y'(t_0)$ to initial point $Y(t_0)$ in the reconstructed phase space of the ECG time series, and the distance is L_0. Then the time evolution for two points is tracked until the distance L_0' exceeds the specified value ε at t_1 at that moment. So $Y(t_0)$ evolves into $Y(t_1)$ at that moment. Another point $Y'(t_1)$ should be found near $Y(t_1)$ that distance L_1 between them is less than ε, and the angle is as small as possible. Repeating the above process until all data points are completed, so the Lyapunov exponent is computed as follows:

$$\lambda_i = \frac{1}{t_i - t_{i-1}} \ln \frac{L_i'}{L_i} \tag{10}$$

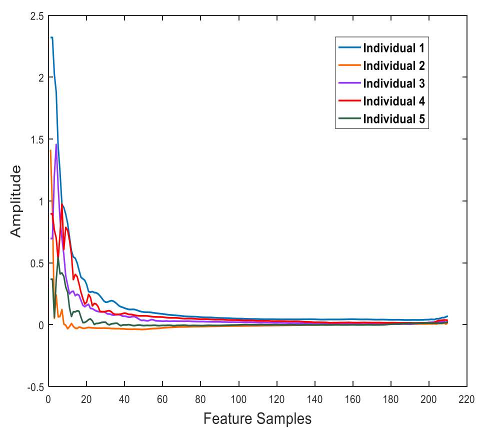

Figure 6(a).

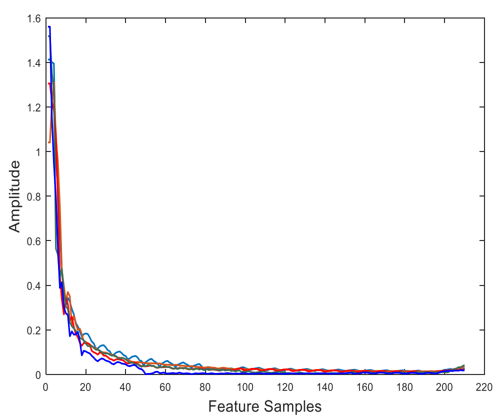

Figure 6(b).

Figure 6. **Comparison for Chaotic Features of Different Individuals and the Same Individual.**

As seen in Figure 6, the chaotic features of the Lyapunov exponent sequence for five different individuals exist as an obvious distinction, and for the same individual is similar. It is proven that the Lyapunov exponent possesses a basic condition for recognizing individuals. Thus, the chaotic features can be as input for the LSTM network classification model to validate the recognition system performance effectively.

3.4 Classification Model based on the LSTM Network

No matter for the morphological low-level features or the chaotic deep-level features, the feature data in sequence are not independent. The LSTM network memorizes previous information and applies it to the calculation of the current output nodes, that is nodes in the hidden layer are connected. Two kinds of extracted features are served as inputs for the LSTM classification network respectively. And the stacked two layers of the LSTM units are adopted as hidden layers for feature sequence modeling, so the model could mine prior information of the ECG signals and provide new ideas for the ECG signals recognition research. The individual classification model structure of deep LSTM neural network in this paper is shown in Figure 7.

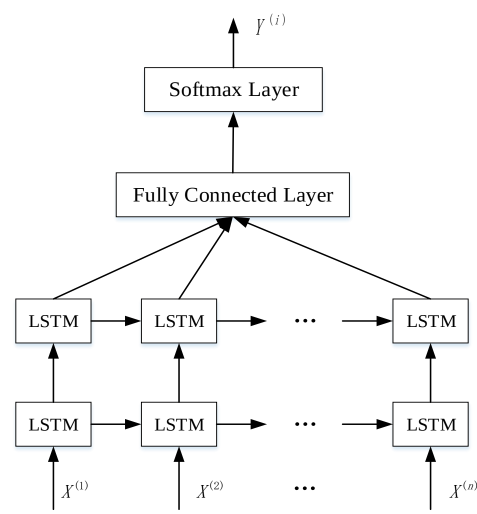

Figure 7. **Deep LTSM Neural Network Classification Model Architecture.**

Let morphological features and chaotic features be the input of the deep LTSM classification model for training, which are extracted based on Section 3.2 and 3.3. As shown in Figure 7, features $X = [X^{(1)}, X^{(2)}, \ldots, X^{(n)}]$ are input into the LTSM network units according to the heartbeats order of time series in turn, where $X^{(i)} = [x_1, x_2, \ldots, x_m]$. The classification model employs stacked two layers of the LSTM structure as hidden layers, output for previous layer of the LSTM should be as input for the next layer. The outputs of the LSTM show each node are integrated by a fully connected layer. As the multi-classification layer, the Softmax layer outputs probability distribution of individual category labels, which is $Y = [Y^{(1)}, Y^{(2)}, \ldots, Y^{(k)}]$. And the dropout module is introduced into the Softmax layer that partial nodes work with a certain probability in the training process. This regularization method can effectively prevent model overfitting. Random initializing network parameters, and the BPTT (Backpropagation Through Time) algorithm is adopted to the fine-tune model parameters layer by layer. The loss function at t moment:

$$E_t(y_t, \hat{y}_t) = -y_t \log \hat{y}_t \quad (11)$$

where $\hat{y}_t$ is actual output value of the Softmax layer, y_t is true output value. So, the whole loss function of system is:

$$E(y, \hat{y}) = \sum_t E(y_t, \hat{y}_t) = -\sum_t y_t \log \hat{y}_t \quad (12)$$

4 RESULTS AND DISCUSSION

4.1 Experimental Database

IN this paper, the deep learning system for the ECG signal identity recognition is constructed by the input layer, stacked LSTM layer, fully connected layer and the Softmax layer. The system is evaluated on the ECG-ID database and the MIT-BIH Arrhythmia database from PhysioNet.

ECG-ID database contains 310 ECG recordings, obtained from 90 individuals. There are 44 males and 46 females, ages from 13 to 75 years. The number of records for each person varies from 2 to 20. Each signal is recorded for 20 seconds and sampling frequency is 500Hz. The ECG recordings are collected during the day or periodically over 6 months. Thus, the ECG signals of this database have individual representation and universality for identity recognition. The MIT-BIH Arrhythmia database contains two-channel ambulatory ECG recordings for 48 individuals. Each signal lasts 30 minutes and sampling frequency is 360Hz. The ECG recordings are collected from a mixed population of inpatients and outpatients with arrhythmia.

4.2 Experimental Results and Analysis

In this paper, the LSTM identity recognition model is applied to different databases, which healthy people in the ECG-ID database and people with heart disease in the MIT-BIH Arrhythmia database, so experiments could effectively evaluate robustness of the heartbeat classification system. The detailed experimental results and analysis are as follows:

The experiment selects 88 individuals from the ECG-ID database, and (2) 20 seconds signals of each individual are respectively selected as the training set and testing set. The 243-dimension morphological feature vectors are extracted to be the input of the LSTM recognition model (Section 3.2). The number of hidden layer nodes is 512. The batch gradient descent algorithm is used for the train model, of which batch size is the number of samples for each gradient descent training. When the batch size is selected small, the convergence effect of the algorithm is not obvious. Appropriately increasing the batch size can reduce the number of iterations for training all samples and improve the algorithm efficiency. Meanwhile, another parameter learning rate is selected so large that the loss function will oscillate, and global optimum will be missed. Therefore, the batch size is set to 50 and learning rate is 0.05 considering the number of iterations and classification accuracy through multiple experimental simulations.

The training accuracy of LSTM recognition network is 100% and the testing accuracy is 80.9% through 20 iterations, which is shown in Table 1 and Figure 8. After 10 training iterations, the training accuracy has been 100% and the heartbeat classification accuracy of the testing set is over 80%.

Table 1. Training and Testing Accuracy of the Deep LSTM Network

Iteration Number	Training accuracy	Testing accuracy	Training time
1	75.07%	59.27%	6.59s
2	92.40%	70.89%	4.93s
3	97.27%	76.99%	4.12s
4	98.15%	77.23%	3.56s
5	99.66%	80.04%	3.21s
6	99.66%	80.04%	3.22s
7	99.85%	79.04%	2.98s
8	99.95%	79.32%	2.94s
9	99.95%	80.37%	2.71s
10	100%	80.90%	2.64s
11	100%	80.04%	2.59s
12	100%	80.66%	2.46s
13	100%	80.37%	2.62s
14	100%	81.04%	2.49s
15	100%	80.32%	2.53s
16	100%	80.42%	2.36s
17	100%	80.66%	2.39s
18	100%	80.47%	2.17s
19	100%	80.80%	2.36s
20	100%	80.90%	2.29s

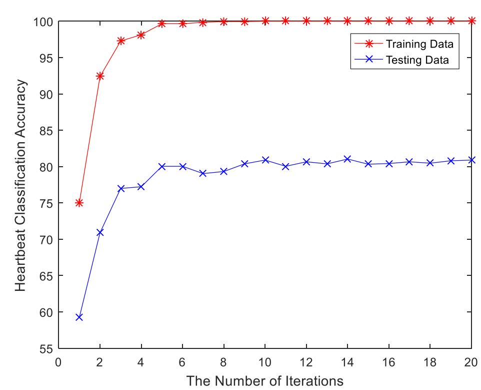

Figure 8. Simulation for Accuracy and Iteration Number of the Deep LSTM Network.

Figure 9 is a simulation diagram of the mean square error and the iteration number for the training process. The mean square error is utilized to evaluate the ability of fitting data for the LSTM classification model. The mean square error is getting smaller as the number of iterations increases, which indicates the predicted neural network model could well describe the training data. The detailed recognition results of 88 individuals are shown in Figure 10 (a) and Figure 10 (b).

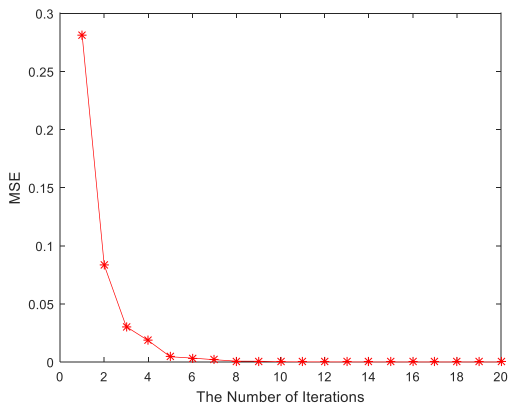

Figure 9. Simulation for the Mean Square Error and Iteration Number.

Taking the first individual for example, the number of heartbeats, which are correctly classified into the first individual is defined as TP, the number of falsely classified into the first is FP. The number of heartbeats, which are correctly classified into the rest of individuals is TN, and the number of falsely classified into the rest is FN. Sensitivity Se is proportion of correctly classified heartbeats to the number of heartbeats of true in this category.

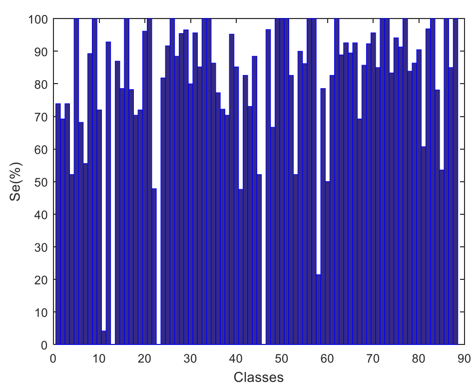

Figure 10(a).

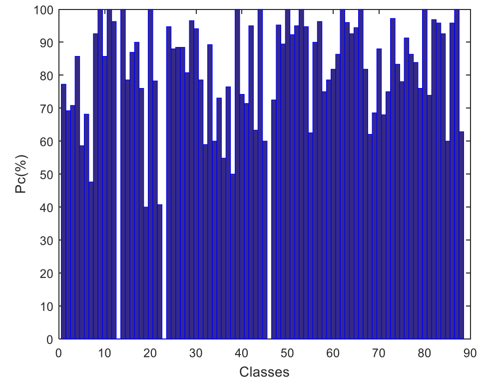

Figure 10(b).

Figure 10. Simulation for the Recognition Rate of all Individual Categories.

$$Se = \frac{TP}{TP + FN} \times 100\% \qquad (13)$$

Precision Pc is proportion of correctly classified heartbeats to the number of heartbeats for being classified into this category.

$$Pc = \frac{TP}{TP + FP} \times 100\% \qquad (14)$$

As shown in Figure 10, Sensitivity Se and Precision Pc are counted for 88 individual categories. The classification ability of the LSTM recognition network for each category is expressed from different perspectives.

Through analysis of the LSTM classification model that is applied on the ECG-ID database, the feasibility of the LSTM network for identifying healthy individuals is verified. Then comparative experiment results between the LSTM network and other classification models are shown in Table 2.

Under the same condition of extracting low-level morphological features of the ECG signals, Table 2 shows that the proposed LSTM recognition network can improve recognition accuracy because of the adequately learning individual information from manually extracted ECG signals features. For training time of ECG-ID database, LSTM recognition network is better than the SVM and BP neural network, but it takes longer than the KNN. However, the KNN algorithm principle is to calculate the distance between the test data and all training data. When the KNN algorithm is applied to the MIT-BIH database with large amounts of data, the training time will

Table 2. Recognition Performance Comparison for Different Classification Models on the ECG-ID Database

	KNN	Gaussian kernel SVM	Linear kernel SVM	BP neural network	LSTM network in the paper
Heartbeat classification accuracy	74.42%	80.47%	75.37%	77.08%	**80.90%**
Identity recognition accuracy	93.18%	94.32%	94.32%	92.05%	**95.45%**
Training time	8.36s	8206.19s	5025.59s	72.23s	61.16s

increase sharply and occupy large memory space, so it can't be applied to practical identity recognition. It's worth noting that the BP and LSTM networks both exist parameters initialization, so actual accuracy will slightly float. To identify 48 arrhythmia individuals from the MIT-BIH database, the low-level morphological feature extraction method is described in Section 3.2, and the 210-dimension Lyapunov exponent sequence is extracted as deep-level chaotic features based on the Wolf algorithm (see Section 3.3). The space reconstruction dimension m for the R-R interval sequences of the ECG signals is 8, and proper delay-time τ is estimated 12. The number of iterations for the LSTM network is 250, so the recognition results of the different classifiers, which input two kinds of features are shown in Table 3.

As shown in Table 3, when applying to the arrhythmia population database, the LSTM deep recognition model also obtains better recognition performance. Whether extracting low-level morphological features or deep-level chaotic features, accuracy of the LSTM network is relatively high, specifically as follows:

When extracting low-level features, 800 heartbeats are taken as the training set and 500 heartbeats are the testing set based on the time series of each individual in turn. Compared with 100 and 60 heartbeats, 800 and 500 heartbeats the LSTM network shows higher accuracy and more stable classification performance under the same parameters setting of classifiers. Classification performance of the proposed model is also optimal when occupying minimum storage space, so the model validity is proven. When extracting the deep-level features, the recognition performance of the proposed LSTM is better than other classification models as well. But overall accuracy is lower than low-level features accuracy. Although the Lyapunov exponent could implement deep expression of signals, the individual information distinctions for the MIT-BIH database signals are not obvious. The combination of the Lyapunov exponent and LSTM neural network builds the chaotic time series recognition model to achieve higher accuracy than other general classification methods no matter how many heartbeats are selected. In conclusion, the robustness of the LSTM network model for different feature inputs can be verified from Table 3.

Table 3. Recognition Performance Comparison for Different Classification Models on the MIT-BIH Database

			KNN	Gaussian kernel SVM	Linear kernel SVM	BP neural network	LSTM network in the paper
Low-level morphological features	Training set: 800 heartbeats Testing set: 500 heartbeats	Heartbeat classification accuracy	89.90%	89.52%	85.22%	90.38%	**92.24%**
		Identity recognition accuracy	100%	100%	97.92%	100%	**100%**
	Training set: 100 heartbeats Testing set: 60 heartbeats	Heartbeat classification accuracy	81.28%	87.81%	83.99%	85.21%	**90.24%**
		Identity recognition accuracy	91.67%	95.83%	93.75%	95.83%	**100%**
Deep-level chaotic features	Training set: 800 heartbeats Testing set: 500 heartbeats	Heartbeat classification accuracy	63.78%	68.31%	62.25%	68.10%	**77.66%**
		Identity recognition accuracy	97.92%	97.92%	95.83%	97.92%	**100%**
	Training set: 150 heartbeats Testing set: 100 heartbeats	Heartbeat classification accuracy	66.67%	65.17%	62.29%	63.63%	**72.44%**
		Identity recognition accuracy	100%	97.92%	95.83%	97.92%	**100%**

5 CONCLUSIONS

THIS paper researches the identity recognition of the ECG signal based on the deep learning model. The deep LSTM neural network model is adopted for beat classification. With deeper learning of the stacked LSTM network model, nonlinear expression ability of the model is gradually enhancing. It not only learned individual information from ECG signals, but also perform effective sparse representation for signals. At the characteristic level, the Lyapunov exponent is introduced as the chaotic feature and is combined with low-level morphological features to be inputs for the LSTM recognition system. Then robustness of the recognition model is validated by the healthy and arrhythmia individual's database. The simulation results show that recognition performance of the deep LSTM neural network model is better than any other classifiers. Heartbeat classification accuracy and identity recognition accuracy are both effectively improved. So, the model stability is verified under conditions of different databases and different types of input features. However, the chaotic features inputs for the LSTM network may occupy a large memory space. And compared to the low-level features, recognition accuracy of chaotic features needs to be improved, so they will be the next direction of future research.

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